Research process and sleep app design lessons learned from the reflective examination of a sleep study

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Introduction

Mobile sleep apps are viewed as promising accessible treatments for insomnia. Using them as data collection tools akin to sleep diaries has also been proposed. Most of these apps, however, have not been developed using evidence-based principles; limited research also exists on their design as research tools (Bhat et al. 2015; Yu et al., 2019).

In the present study, we explored the opportunities and challenges experienced when using a mobile app for research with our own team's research study as the unit of analysis. This is an intrinsic case study (Stake, 1995), which can inform other researchers on how to approach their studies when using sleep apps in research as an intervention (treatment) or research tool (data collection).

Context: The Somnotest Study
Data were collected during a larger study, designed to test the effects of serial diverse imagining (SDI, a form of cognitive shuffling; Selham et al., 2018), using SomnoTest, on insomnia. In that study, the data of 19 control participants and 15 treatment participants, aged 18 to 30 years, all of whom reported insomnia, were analysed. Participants were assigned to one of two app conditions. Group 1 participants heard a countdown from 99 to 1, and Group 2 were prompted to visualise randomly selected brief scenes read by the app at eight-second intervals (SDI).

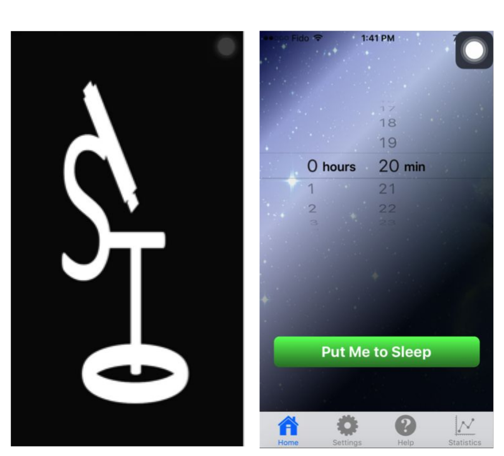
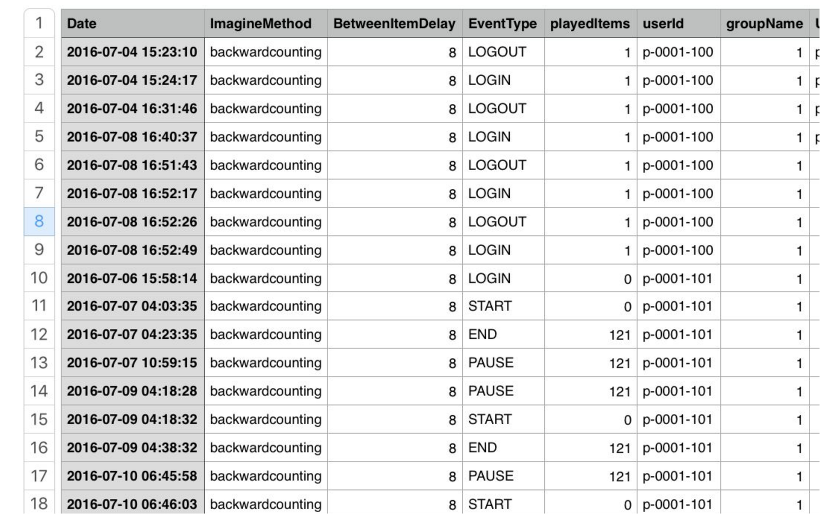


Figure 1. SomnoTest mobile app

Method and Materials

Case study

Using a qualitative approach involved the direct interpretation (Stake, 1995) of participants' patterns of mobile app usage, based on actions recorded (i.e., press start, end, pause, resume, or cancel; time stamp; count of played items), and the reorganization of user actions into tables (visualisation; tabulation) to identify usage patterns. The researchers' reflection notes on their respective experiences in analyzing the data were analysed as *lived experiences* that could inform more effective data analysis procedures when working with raw data from mobile apps, with the objective of deriving themes to inform improved research practice in this context. Thematic analysis of these experiences was also conducted to reveal exemplars of situations that researchers could face.



Raw data for all control (*n*=23) and intervention (*n*=31) participants prior to data cleaning

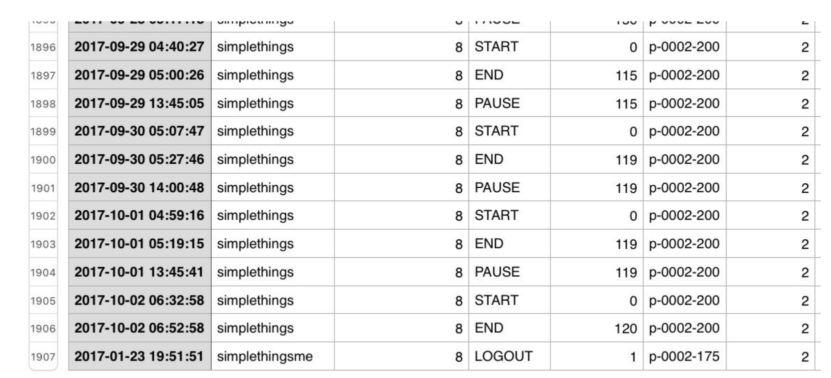


Figure 2. Raw data for all those who participated in the study, including those whose data were not used in the larger study's analysis. 1907 total actions were logged. The initial step in data cleaning involved ensuring that only those participants who submitted sleep diaries are included in the analysis.

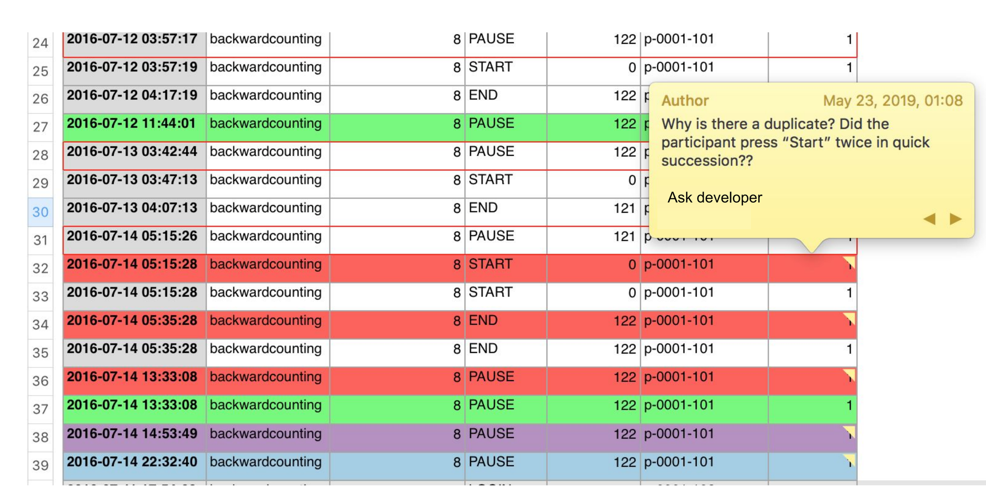


Figure 3. Step two in the analysis involved a line-by-line analysis of each action, taken by participants or recorded by the app, to identify patterns as part of the data cleaning process.

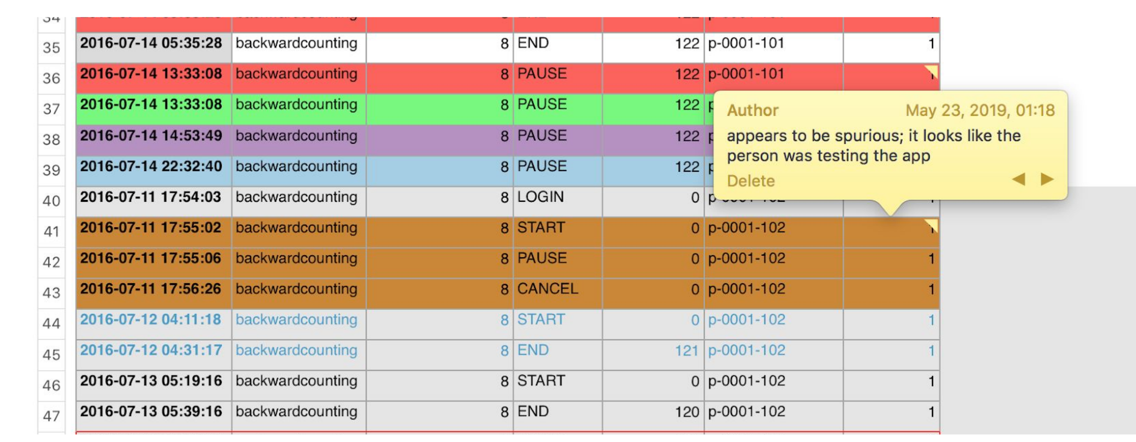


Figure 4. Only through time-intensive, line-by-line analysis could spurious data patterns be discerned.

Findings

Four themes:

1) Unreliability of sleep diaries when triangulated against SomnoTest data, given that 9 participants had not used the app as claimed;

2) Complex, intensive qualitative analysis is needed to identify valid data in an unstructured data set;

3) Importance of visualisation when examining data to uncover patterns;

4) Identification of "fans" who continue to use the app when not required during the study and after their participation in the study.

Our findings reveal that data cleaning involves intensive line-by-line and case-by-case analysis of participant data, which proved challenging with 34 participants and would prove prohibitive for larger scale studies.

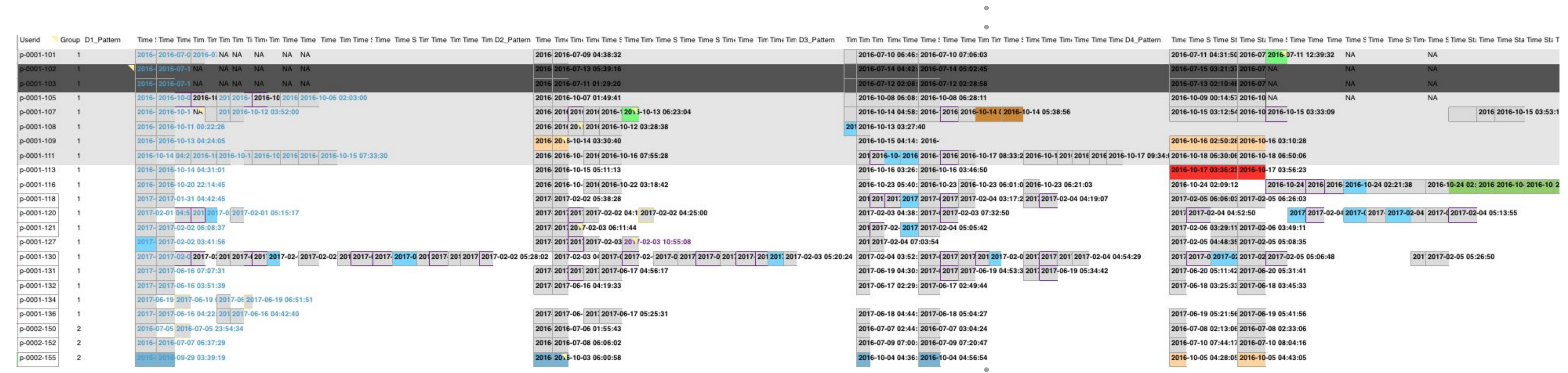


Figure 5. Step 3 involved identifying emerging patterns from cleaned data, in terms of participants' mobile app usage, through the creation of a spreadsheet, which provided a visual representation of the data. This step facilitated easy identification of participants who did not use the app as stated in their sleep diaries as well as of other patterns of usage (e.g., heavier app use throughout the night).

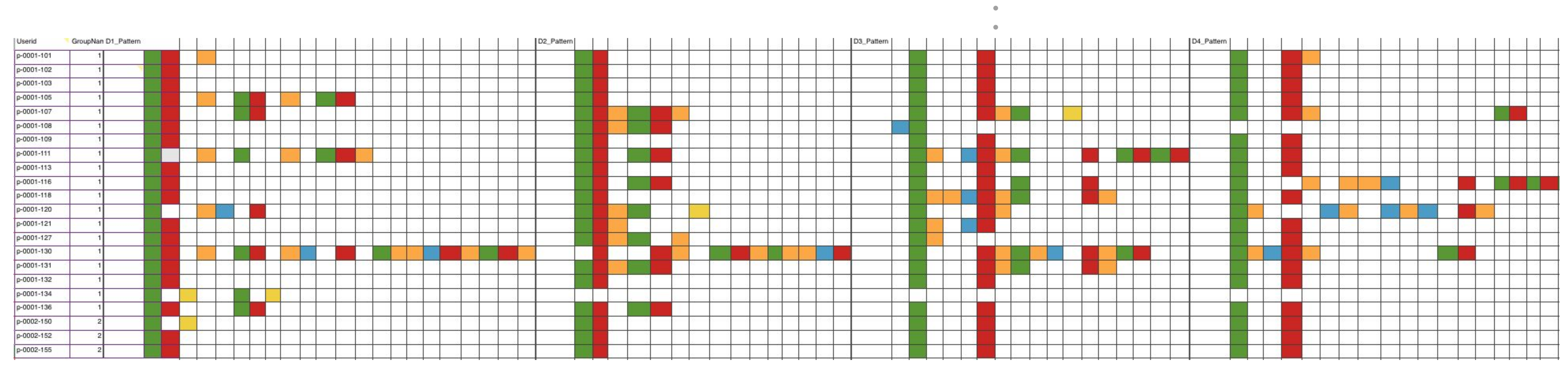


Figure 6. Conceptual mockup for an *app usage visualisation feature* to support researchers in identifying usage patterns and anomalies in user actions (green = start; red = end; orange= pause; yellow = cancel; blue= resume)

This feature could be used to identify more efficiently the usage patterns of participants through a visual representation of the collected data, making use of data analytics to screen out spurious data patterns. This mockup reflects similar data patterns to that identified in Figure 5.

Discussion

Our findings reveal that using sleep apps in collaboration with sleep diaries could lead to greater certainty that sleep diary data have been accurately reported, especially if participants are aware that their mobile usage patterns will be tracked and compared against diary data. From a research methodology and administration perspective, this would entail working closely with the mobile app development team to ensure that timely identification of non-compliance with study procedures can be made.

Although sleep app data have the potential to contribute to our understanding of mobile use in naturalistic conditions, the unstructured form of the data collected will prove too costly to analyse for many researchers, unless more efficient means of data analysis can be developed.

Data science and data analytics can provide direction; however, the initial identification of typical and valid sequences of user actions must first be identified so that effective algorithms can be developed. These algorithms can then be used to create visualisations that researchers can use to identify patterns of interest in the data more efficiently and effectively. Another challenge will also be to ensure that algorithms do not limit insights to only those patterns identified prior to data collection, thereby limiting potential new insights that could potentially be gleaned.

Conclusion

Informing participants that app data will be triangulated against sleep diaries during data collection and analysis may ensure greater accuracy of participant-provided sleep diary data.

The development of an algorithm that can efficiently filter valid data usage patterns would facilitate data analysis and researchers' experience. This would increase sleep app usability as a treatment and research tool. Developing a process for increasing efficiency in data analysis is necessary to exploit the advantages of large-scale data collection that a sleep app makes possible.

This study, although preliminary, provides insights on how to improve research practice in the context of mobile app usage in sleep research, in terms of using the app as both intervention and research tool. Insights in the conceptualisation of a visualisation feature that could be developed to provide more efficient identification of usage patterns has also been proposed.

References and conflict of interest

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COI disclosure: Luc P. Beaudoin is a director of CogSci Apps Corp. and owner of CogZest. Both of these Canadian businesses develop products based on his affective / cognitive science. These include books, software, and training services.

Acknowledgments: Drs. Guloy and Beaudoin would like to thank Dr. Phil Winne for introducing us, many years ago, to the importance of software logging and analysis for scientific research.